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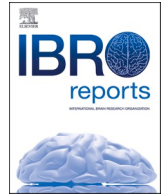
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Research Paper

Large effects of brief meditation intervention on EEG spectra in meditation novices

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ABSTRACT

This study investigated the impact of a brief meditation workshop on a sample of 223 novice meditators. Participants attended a three-day workshop comprising daily guided seated meditation sessions using music without vocals that focused on various emotional states and intentions (open focus). Based on the theory of integrative consciousness, it was hypothesized that altered states of consciousness would be experienced by participants during the meditation intervention as assessed using electroencephalogram (EEG). Brainwave power bands patterns were measured throughout the meditation training workshop, producing a total of 5616 EEG scans. Changes in conscious states were analysed using pre-meditation and post-meditation session measures of delta through to gamma oscillations. Results suggested the meditation intervention had large varying effects on EEG spectra (up to 50 % increase and 24 % decrease), and the speed of change from pre-meditation to post-meditation state of the EEG co-spectra was significant (with 0.76 probability of entering end-meditation state within the first minute). There was a main 5 % decrease in delta power (95 % HDI = [−0.07, −0.03]); a global increase in theta power of 29 % (95 % HDI = [0.27, 0.33]); a global increase of 16 % (95 % HDI = [0.13, 0.19]) in alpha power; a main effect of condition, with global beta power increasing by 17 % (95 % HDI = [0.15, 0.19]); and an 11 % increase (95 % HDI = [0.08, 0.14]) in gamma power from pre-meditation to end-meditation. Findings provided preliminary support for brief meditation in altering states of consciousness in novice meditators. Future clinical examination of meditation was recommended as an intervention for mental health conditions particularly associated with hippocampal impairments.

1. Introduction

Mental stress is a global health epidemic being linked to more than 23 million worldwide deaths each year (Fink, 2016; Go et al., 2004). Chronic stress is associated with cognitive impairments to the hippocampal region of the brain that regulates memory and learning (Hains et al., 2009; Kooij et al., 2014) and with negative physiological effects including increased inflammation and reduced immunity (Marsland et al., 2017). A range of mindfulness-based techniques have been designed to reduce stress and enhance quality-of-life indicators (Bohlmeijer et al., 2010; Shapiro, 2009). In particular, there is increasing research interest on the effect of meditation on whole-health benefits (e.g., as a catalyst to improve immune function; Davidson et al., 2003; Jacobs et al., 2011). Meditation is a conscious and complex cognitive

process, involving concentration and receptive attention (Tang et al., 2015). Examples of meditation include mantra meditation, tai chi, and chi gong (Ospina et al., 2007). Meditation is considered a mechanism that can elicit altered states typically associated with unconscious brain function (Shapiro, 2009). Focused-attention meditation practices require sustained attention on a specific range of inner or outer experience. While open-awareness, open-monitoring, and mindfulness meditation practices incorporate a broader attentional spotlight on an array of dynamic stimuli (Cahn and Polich, 2006; Lutz et al., 2008). Further still, guided meditation approaches typically begin with relaxation directed by another expert that guides the meditator toward specific inner experiences (e.g., imaginative situations, thought processes). Guided meditation is considered particularly beneficial because the nature of instructions tend to relate to some specific purpose, such as

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healing or self-improvement. Examples of meditative goals include creating prosperity, improving relationships, fostering forgiveness, and evoking higher states of consciousness (Moral, 2017).

Growing evidence suggests that meditation offers wide-ranging physiological and psychological benefits. Meditation practices are associated with enhanced executive function and working memory together with improvements in mental health condition severity (e.g., anxiety, depression, eating disorders; (Fox et al., 2014; Perich et al., 2013; Shapiro, 2009; Vøllestad et al., 2012; Williams et al., 2014).

Meditation encompasses a broad set of psychosomatic practices that are designed to enhance attentional regulation toward self-created mental images (interoceptive or exteroceptive foci) and to optimize the processing of present-moment experiences (Jain et al., 2015; Robins et al., 2012). These capabilities have been mapped to corresponding areas in the brain including the dorsal system (voluntary, top-down orienting) and the ventral system which is implicated in stimulus-driven, bottom-up attention (Shapiro, 2009). Studies using functional magnetic resonance imaging (fMRI) have helped delineate systemic maps of the physiological dimensions associated with meditation (Church, 2013). In particular, modern electroencephalogram (EEG) mapping and neuroimaging techniques have enabled the examination of differential brain function across a continuum of states including meditative experiences (Barinaga, 2003; Cahn and Polich, 2006).

Distinct cognitive networks are linked to conscious processing tasks during attentional tasks (e.g., orientation, conflict monitoring; Davidson et al., 2003) and to objective and receptive attentional-basis of mindfulness practice (e.g., non-judgement, acceptance; (Anderson et al., 2007; Shapiro and Schwartz, 2000). Increased attentional control has been observed in individuals with advanced meditation practice (Moore and Malinowski, 2009). One study examined meditation competence in participants with varying levels of meditation experience using EEG data. Event-related potentials (ERPs) were assessed during a stimulus discrimination and attention activity (Atchley et al., 2016). All participants discriminated between target ‘tones’ with the use of ERP priming. Further, no performance difference was observed between novice and experienced meditator groups. This was one of the first studies to suggest that proficiency in attentional training using meditation practice can be achieved relatively quickly.

Theoretical models of consciousness suggest that conscious and unconscious processes depend on distributed neuronal components acting in functionally integrated ways (Schutter et al., 2004; Smith, 2012). Meditation is, therefore, thought to offer a unique vehicle for examining these processes. That is since both conscious and unconscious brain functioning simultaneously, meditation provides an opportunity to observe the transition from a normal awake state to an alert yet altered state of consciousness (Davidson et al., 2012). States of consciousness are described as conditions that differ qualitatively from others by the presence of, or conditions and characteristics that are, absent in other states (Tart, 1972). Since states of consciousness play a critical role in forming human experience across a range of cognitive and behavioural functioning, examinations of the underlying conscious and unconscious brain mechanisms are crucial (Merrick et al., 2014; Vieten et al., 2018; Winkelman, 2011). Such insights may offer clinical outcomes that can be directed to further assist psychological and physiological distress.

The model of integrative consciousness has evolved from the theory that physiological mechanisms of “transcendent states” are based on a common neurochemical pathway involving the temporal lobe (Mandell, 1980). From this theoretical perspective, meditation practice is thought to produce serotonin inhibition to the hippocampal cells, which in turn increases cell activity and the manifestation of hippocampal septal slow-wave EEG activity (i.e., alpha, delta, and theta) that imposes a synchronous slow-wave pattern across the lobes (Winkelman, 2010, 2011). Integration is manifested in the entrainment of the frontal cortex by highly coherent and synchronized slow-waves discharges that emanate from the limbic system and related lower-brain structures. These entrainments occur at a variety of frequencies, but two

predominant patterns are synchronised slow-wave theta bands (3–6 cycles per second) and high-frequency gamma oscillations (40+cps). These synchronised brain wave patterns are referred to as an integrative mode of consciousness (Winkelman, 2011).

Prior research has examined meditation effects in clinical samples and individuals with extensive meditation expertise (e.g., Buddhist monks, shamans, and practitioners with greater than 10 years’ experience mindful practice, Flor-Henry et al., 2017; Tang et al., 2015). In particular, differential brain activations have been observed in experts during meditation, as a result of various styles of meditation frequently measured via EEG. Further, physiological measures of naïve meditators have mirrored those of highly experienced meditators after a single meditation session (Fennell et al., 2016). However, little research has offered an electrophysiological examination of the meditative experience in individuals with limited meditation experience and with a guided meditation approach. To develop this research gap, the current study aimed to examine the impact of intensive meditation practice (2–4 h of meditation practice per day) on a sample of novice meditators. Factors of the intervention (including environment and meditation approaches) were optimized to accelerate learning amongst participants. The current study aimed to assess participants’ altered states of consciousness during meditation by comparing the pattern of brainwave power bands at each meditation end-point with baseline measures (i.e., alpha, delta and theta oscillations) and through assessment of high-frequency gamma synchronization. Drawing on the theory of integrative consciousness (Winkelman, 2011), it was hypothesized that altered states of consciousness would be detected by altered patterns of brainwaves across each meditation in the sample of novice meditators.

2. Materials and method

2.1. Participants and procedure

The initial convenience sample consisted of 468 participants aged 19–83 years ($M = 50.56$, $SD = 14.52$), of which 312 were female (71.4 %) and 125 were male (28.6 %). All participants provided written consent to participate in the study. Participants were meditation novices or had limited previous exposure to forms of guided meditations. All participants attended meditation training workshops delivered by Dr Joseph Dispenza, D.C. held in various North American locations. The meditation training, known as “Advanced Workshop”, comprised two-three daily sessions across three days. In each session, participants attended psychoeducation-based talks (e.g., lecture about the role of hormones in stress; Dispenza, 2014) and participated in a guided seated meditation to music (without vocals and with open focus) that was approximately 60-min in duration. EEG brainwave data was recorded for each participant throughout the meditation session, with pre-meditation EEG data compared to end-point meditation EEG data for each session of the meditation training program.

2.2. EEG analyses

EEG was measured using a standard 10/20 19-electrode array. There was a main effect of meditation on EEG spectra, and an interaction between electrode site and mediation condition. For example, Fig. 7 shows this interaction colour coded to show the most negative and positive changes in spectra from meditation. However, the model indicated that there were no evidence of systematic interactions between electrode location and meditation technique, indicating that the sources may be the same across the meditation techniques but the intensity and combination of band power changes differed between techniques. The EEG setup process required 10-min per participant, in which head circumference measures were matched to an EEG cap (small, medium, and large sizes). The caps were calibrated approximately two-inches above the eyebrow and followed a line beginning at the middle of the forehead and continued around the head to meet at the designated beginning

point. Baseline recordings were obtained, which included eyes closed (4-min) and brain on task (4-min) before meditation sessions were recorded.

2.3. Meditation types

Across the three-day workshop, 468 participants engaged in approximately three meditations per day (see Table 1), which produced a total of 5616 EEG scans. The seated guided meditation, led by the second author emphasized breathing, visualization, and focused concentration (internalized attention).

3. Results

3.1. Pre-processing

Given the variability in pre-processing and montages, data from headsets recordings of linked ear reference with the 0.5–80 Hz band pass pre-processing was used, which reduced the sample to 283 participants. Data for 60 participants were removed due to a short duration of in-session recordings (< 10 min) as durations of less than 10 min were not long enough to be viable for the neural dynamics assessment. This left a final sample of 223 participants. EEG data were exported in EDF format and imported into MNE-Python (Version 17.1; Gramfort et al., 2013, 2014) for subsequent analysis. The PREP pipeline was used to detect channels corrupted by noise (Bigdely-Shamlo et al., 2015) with all non-working electrodes interpolated via the Spherical splines (Perrin et al., 1989, 1990). The data were bandpass filtered to 1–50-Hz with FIR filter (Rabiner et al., 1978). Potential eye blinks were detected using a moving median, with a median between 30–300 microvolts with a window of 15 samples (60-ms) labelled as a blink, as measured at Fp1 and Fp2 electrodes. The data were transformed by the surface Laplacian (via spherical interpolation) to provide a more robust reference-free signal (Kayser and Tenke, 2006). The data surrounding the eye blink events were segmented into –500 to 500 ms epochs. Independent component analysis was conducted using the Picard algorithm (Ablin et al., 2018) to isolate and removed EOG artefacts present in the data by selecting the component with the largest absolute Pearson r correlation coefficient to the eye blink epochs via *find_bad_eog* function in MNE-Python. The last five minutes of pre-meditation and meditation recordings were used to compare the effects of the various meditation

Table 1
Meditation Sessions by Time of Day.

S	Time	Meditation Type
Day 1 Type 1 (D1T1)	Morning (9.00am) Meditation	Focus on elevated emotion levels and liberating energy in body to attune, align and connect the associated chakra centres
Day 1 Type 2 (D1T2)	Midday Meditation (12 noon)	Focus on emotion of gratitude
Day 1 Type 3 (D1T3)	Afternoon Meditation (3.00 pm)	Focus on surrendering
Day 2 Type 1 (D2T1)	Morning Meditation (9.00am)	Focus on elevated emotion levels and liberating energy in body to attune, align and connect the associated chakra centres
Day 2 Type 2 (D2T2)	Midday Meditation (12 noon)	Focus on a specific intention to materialise a specific event in life
Day 2 Type 3 (D2T3)	Afternoon Meditation (3.00 pm)	Focus on elevated emotion and a sense of wholeness and oneness with the world (via an open focus meditation)
Day 3 Type 1 (D3T1)	Early Morning (6.30am) Meditation	Focus on elevated emotion levels and liberating energy in body to attune, align and connect the associated chakra centres
Day 3 Type 2 (D3T2)	Mid-morning Meditation (10.00am)	Focus on creating a future intention
Day 4 (D4T1)	Very early morning (4.00am) Meditation	Focus on moving energy through the body to the brain to activate the pineal gland to induce a mystical experience (seated and laying down meditation)

types on EEG spectra, and the EEG recorded during meditation was used to assess the neural dynamics of meditation. The R package *ggplot2* and *MNE-Python* were used to create the figures (Hadley and Sievert, 2016).

3.2. Model fitting

Bayesian parameter estimation was used to assess results (McGill et al., 2017). This analysis was selected since the intentions of the experimenter are stated explicitly via the model and the prior distributions. Full distributions for credible values for all parameters in the model were provided rather than single values. As this procedure does not use *p* values or confidence intervals, Bayesian parameter estimation is considered to provide more information than null hypothesis significance testing (Kruschke, 2013). Posterior distributions were summarized with their median and highest density interval (HDI) (Kruschke and Liddell, 2015). The HDI contains the 95 % most likely values of the distribution. R version 3.5.1 (R Core Team, 2018) was used for all statistical analyses. Stan 2.17.0 (Carpenter et al., 2017) with the RStan 2.17.3 (Stan Development Team, 2018) interface to fit all models. Stan estimates the posterior distribution using a Hamiltonian Monte Carlo (HMC) procedure. For each model, four chains concurrently drew 2000 samples, 1000 of which were warm-up. The resulting sample size was 4, 000. The posterior samples for each parameter were evaluated for convergence via inspection of both the trace plots and the Gelman–Rubin \hat{r} statistic (Gelman and Rubin, 1992), where \hat{r} near 1.00 indicate that the chains have converged.

3.3. Frequency comparison via machine learning

To examine whether there was an effect of meditation on the EEG frequency spectra, machine learning classifiers were individually trained to discriminate between before meditation data and the last five minutes of meditation (condition). A Riemann-geometry based classifier (Congedo et al., 2017) using the co-spectra of the EEG between four and 45-Hz (250-ms hanning window, 75 % overlap, 4-Hz resolution) for 2-s non-overlapping epochs for pre-meditation and the end-meditation data was used. Riemannian-geometry based classifier was selected due to this type of classifier being among the best in terms of performance in BCI classification, ease of implementation, and good generalisation capability compared other options such as deep learning (Lotte et al., 2018). Additionally, the performance during validation was very high and thus was suitable for the purpose of estimating the neural dynamics of the meditation techniques. The classifier used tangent-space logistic regression (Congedo et al., 2017) to discriminate between the two states. Random-split (75 % train, 25 % test) 10 fold-cross validation was used to estimate performance measured by the classifier’s confusion matrix. To estimate overall performance a Multinomial-Dirichlet hierarchical model was fitted to the mean confusion matrix of each participant (See model description). Confusion matrix estimates were then summarized into accuracy and proficiency measures (White et al., 2004). Accuracy and proficiency were calculated from the confusion matrix using the standard procedure: Accuracy, by taking the sum of the True positives and True negatives divided by the total of the confusion matrix and proficiency, by calculating the mutual information of the expected and the predicted outcomes, divided by the entropy of the expected outcomes (Caelen, 2017; White et al., 2004).

3.4. Frequency comparison model description

We were interested in how well the classifiers discriminated pre and end-meditation states, and whether there were any differences in performance between meditation techniques. A participant classifier’s confusion matrix, $\vec{C_p}$, was modelled as a random sample from a multinomial distribution:

$$\vec{C_p} \sim \text{Multinomial}(\vec{\theta_p})$$

where $\vec{C_p}$ estimated the probabilities of true negatives, false positives, false negatives, and true positives for an individual classifier. $\vec{C_p}$ was given a Dirichlet prior:

$$\vec{\theta_p} \sim \text{Dirichlet}(\vec{\theta_t} \times \kappa_t)$$

where $\vec{\theta_t}$ measured the group probabilities for each cell in the confusion matrix for a particular meditation technique and κ_t estimated the concentration of $\vec{\theta_t}$. $\vec{\theta_t}$ was also given a Dirichlet prior:

$\vec{\theta_t} \sim \text{Dirichlet}(\vec{\theta_g} \times \kappa_g)$ where $\vec{\theta_g}$ estimated overall performance and κ_g how closely the different meditation techniques matched the $\vec{\theta_g}$ estimate. All κ_x parameters were given diffuse gamma priors:

$$\kappa_x \sim \text{Gamma}(2, 0.1)$$

3.5. Frequency comparison results

The model indicated that the classifiers were extremely accurate, with the overall accuracy of 97 % (95 % HDI = [0.96, 0.98]) and proficiency of 0.81 (95 % HDI = [0.75, 0.86]). There was no evidence for a credible effect of meditation technique on accuracy or proficiency as displayed in Figs. 1 and 2. This invariance to meditation technique is important for the following neural dynamics analysis as differences between classifier performance could confound the results.

3.6. Meditation neural dynamics

Data during meditation was epoched in the same manner as the frequency comparison analysis and then classified as like pre-meditation or end-meditation. This created a binary time series for each individual, providing insight as to when meditation changed the EEG co-spectra and how the different techniques impacted this dynamic relationship. Logistic regression was applied to each participants' classification time series which summarised the series into intercept and slope pairs. These pairs were assessed with a Bayesian general linear model to quantify the effectiveness of each meditation technique at inducing the end-state EEG co-spectra (see model description).

3.7. Neural dynamics model description

We were interested in quantifying how meditation changes EEG co-spectra and how effectively various meditation techniques facilitate this change. To assess this change logistic regression was carried out, producing intercept and slope values for each participant. Participants' intercept and slope, were modelled separately, $y_{p[i]}$, as a draw from a Normal distribution:

$$y_{p[i]} \sim \text{Normal}(\mu_{[i]}, \sigma_{[i]})$$

Where μ was derived from the linear combination:

$\mu_{[i]} = \beta_0 + \beta_t \times x_{t[i]}$ where β_0 parameter estimates the group central tendency whereas β_t measured the effect of technique on intercept and slope. β_0 was given a normal prior centred on the mean of the data, with 10 times the standard deviation of the data:

$$\beta_0 \sim \text{Normal}(\bar{y}_{[i]}, \text{Sd}(y_{[i]})) \times \text{Sd}(y)$$

σ parameter was given diffuse gamma prior as per :

$$\sigma_{[i]} \sim \text{Gamma}(2.0, 0.1)$$

β_t was given a sum-to-zero constraint by zero-centring a simplex vector, $\vec{s}_{t[i]}$, and multiplying it by a scaling variable, σ_t :

$\beta_{t[i]} = \sigma_{t[i]} \times (\vec{s}_{t[i]} - \frac{1}{n_t})$ where the simplex was given a uniform Dirichlet prior and the scale given a gamma prior:

$$\vec{s}_{t[i]} \sim \text{Dirichlet}(\vec{1})$$

$$\sigma_{t[i]} \sim \text{Gamma}(2.0, 0.1)$$

Priors were chosen to be weakly informative to the scale of the data.

3.8. Neural dynamics results

Results indicated that there was insufficient evidence to detect the effect of meditation technique on the logistic regression intercept values (see Fig. 3). However, the intercepts for each meditation technique were quite large (see Fig. 4), where the probability of EEG-co-spectra being like the end-meditation state was 0.76 (95 % HDI = [0.71, 0.81]) at the start of meditation.

There was a significant effect of meditation technique on logistic regression slope with D2S2 0.0231 larger than the slope of D3S2 (95 %

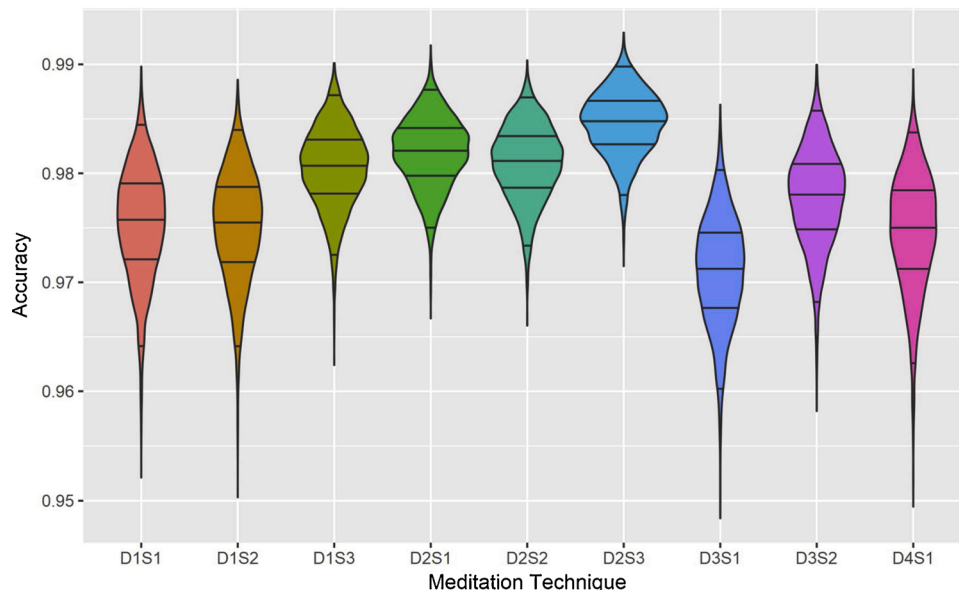


Fig. 1. Shows violin plots of posterior estimates for classifier accuracy by meditation technique, indicating invariance of accuracy across meditation techniques.

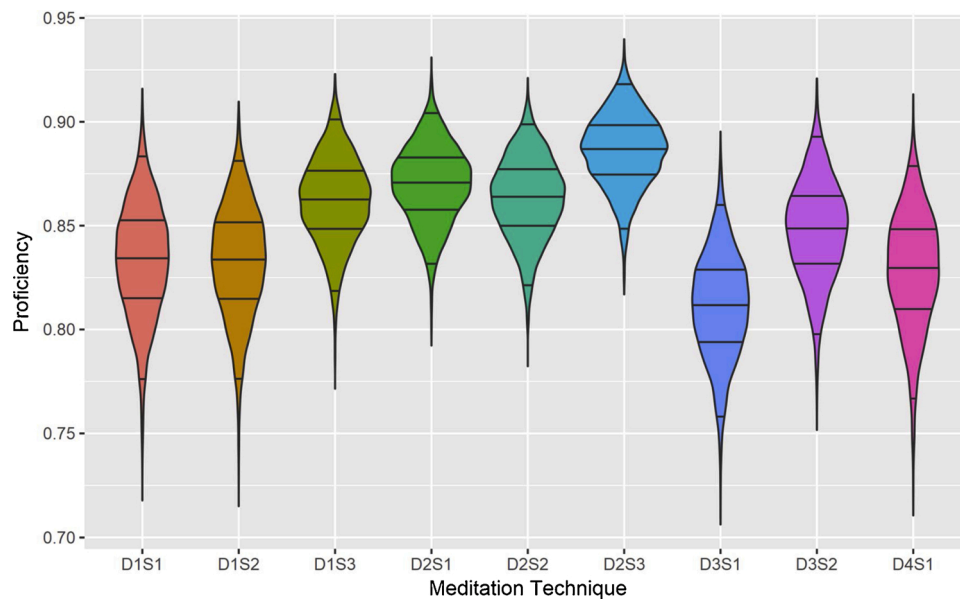


Fig. 2. Depicts violin plots of posterior estimates for classifier proficiency by meditation technique, indicating invariance of proficiency across meditation techniques.

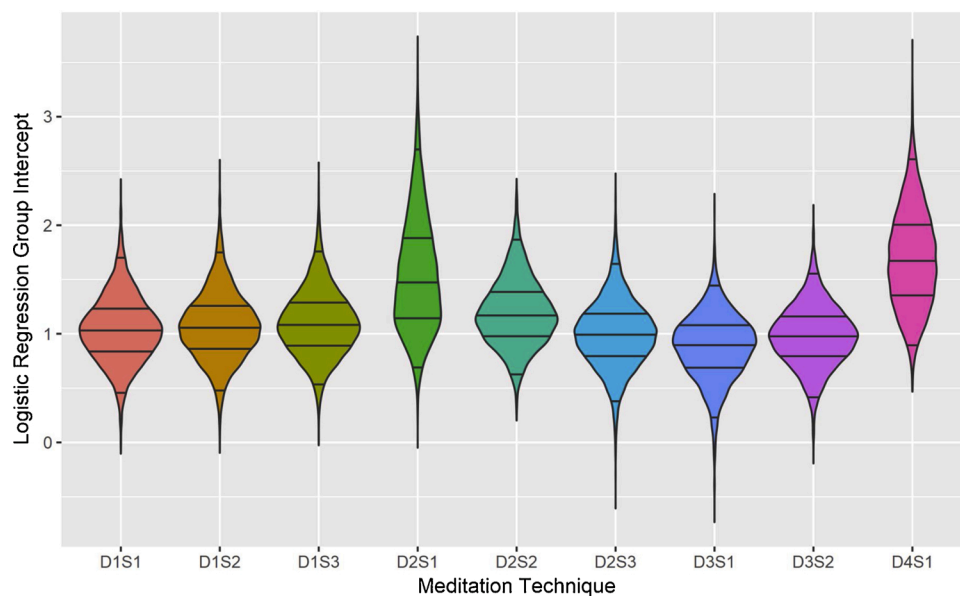


Fig. 3. Shows a violin plot of the posterior estimates of logistic regression intercept of classification series for each meditation technique. The intercepts are quite large indicating changes in EEG co-spectra occurred quite quickly and the figure also depicts the invariance of intercept across techniques.

HDI = [0.0003, 0.04472], zero not included). This suggests that D2S2 induced the meditation-end state faster than D3S2 technique, as displayed in Fig. 5.

3.9. Power band analysis

Pre-meditation and end-meditation data were epoched to 2-s non-overlapping windows and their power spectral density (PSD) were estimated using the multitaper method (Thomson, 1982). Band power were derived from PSD summing over 1–4 Hz for Delta, 4–8 Hz for theta, 8–13 Hz for alpha, 15–25 for beta, and 35–45 Hz for gamma using Simpson's rule for integration. The mean was recorded for each participant, at each electrode, both for pre-meditation and end-meditation conditions. EEG power spectra are generated predominantly from cortical sources with some input from subcortical structures

(see Buzsaki, 2006) with all canonical power bands related to meditation (Lee et al., 2018).

3.10. Power band analysis model description

We were interested in measuring the effect of meditation on EEG power bands and whether there were any differences between meditation types. Each power band, y , was modelled separately, as a random draw from a log-normal distribution:

$y \sim \text{lognormal}(\mu, \sigma) \sim \text{log-normal}(\mu, \sigma)$
where σ represented the standard deviation, and μ the mean estimate:

$$\mu = \beta_0 + \beta_p \times x_p + \beta_e \times x_e + \beta_c \times x_c + \beta_t \times x_t + \beta_{e \times c} \times x_{e \times c} + \beta_{e \times t} \times x_{e \times t} + \beta_{c \times t} \times x_{c \times t} + \beta_{e \times c \times t} \times x_{e \times c \times t}$$

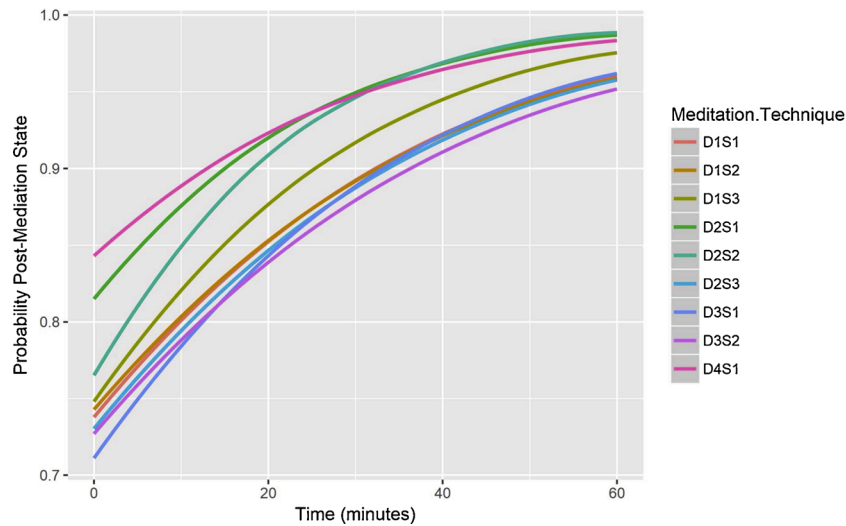


Fig. 4. Shows the median estimates for logistic regression of classification series for each meditation technique.

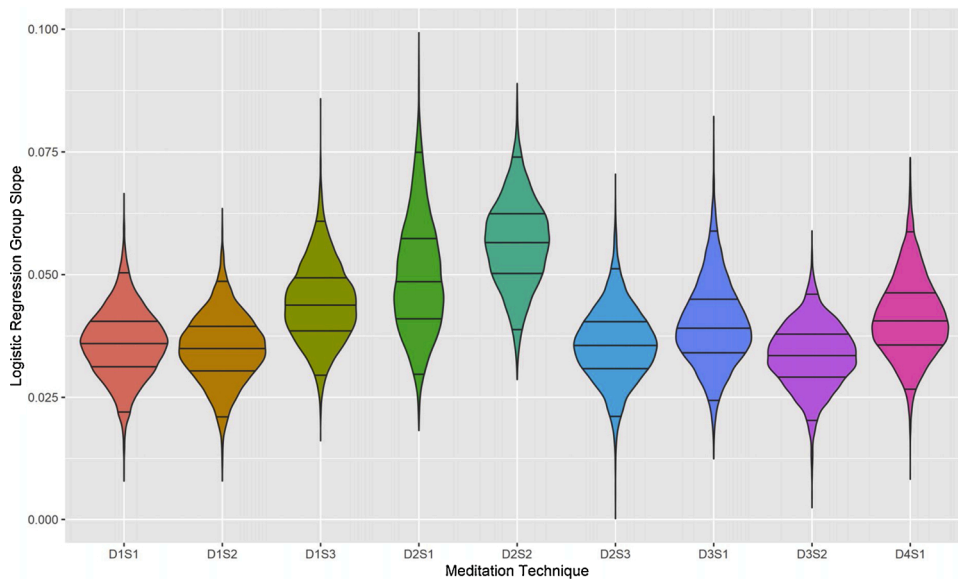


Fig. 5. Illustrates a violin plot of the posterior estimates for logistic regression slopes of classification series for each meditation technique. D2S2 has a larger slope than D3S2 indicating end-meditation EEG co-spectra was achieved more rapidly for D2S2.

where β_0 is the overall baseline, β_p is baseline specific to a participant, β_e estimates the effect of electrodes, β_c measures the effect of meditation condition (before or end-meditation), t is parameter for the effect of meditation technique. The interaction parameters $\beta_{e \times c}$ measured electrode within each condition, $\beta_{e \times t}$ estimated the effect of electrode within each meditation technique, $\beta_{c \times t}$ quantifies the interaction between condition and meditation technique, and $\beta_{e \times c \times t}$ is the parameter for the three-way interaction between electrode, condition and technique. The baseline parameter was given a normal prior:

$\beta_0 \sim \text{Normal}(\text{mean}(\log(y)), 10 \times \text{Sd}(\log(y)))$ whereas each other factor and interaction parameters were given sum-to-zero constraints using the k-1 procedure:

$$\alpha_x \sim \text{Normal}(0, \sigma_x) \beta_{x[1:k-1]} = \alpha_x$$

$$\beta_{x[k]} = -\sum \alpha_{x[i]}$$

With interaction parameters constrained to sum to zero across each predictor. σ_x parameters were drawn from a diffuse gamma distribution,

given the log scale of the model:

$$\sigma_x \sim \text{Gamma}(1.64, 0.32)$$

$\beta_{e \times t}$, $\beta_{e \times c}$, and $\beta_{e \times c \times t}$ were given fixed standard deviation of 1 to avoid problematic shrinkage which was adversely affecting the Hamilton Monte Carlo sampling.

3.11. Delta

There was a main 5 % decrease in delta power (95 % HDI = [−0.07, −0.03]) after meditation compared to pre-meditation. There was also a main effect of meditation where D1S2 had 72 % higher delta power than D2S1 (95 % HDI = [0.04, 1.48]). Furthermore, a credible interaction between the meditation technique and condition was found (see Fig. 6). D1S2, D3S1, and D4S1 had the highest increase (16 %, 18 %, and 18 % with 95 % HDI = [0.07, 0.25], [0.1, 0.26], and [0.08, 0.28], respectively), D2S2 had no evidence of a change in power (95 % HDI = [−0.08, 0.05] containing zero), and D1S1, D1S3, D2S1, D2S3, and D3S2 showed a decrease in delta (−12 %, −16 %, −24 %, −18 %, and −12 % with 95

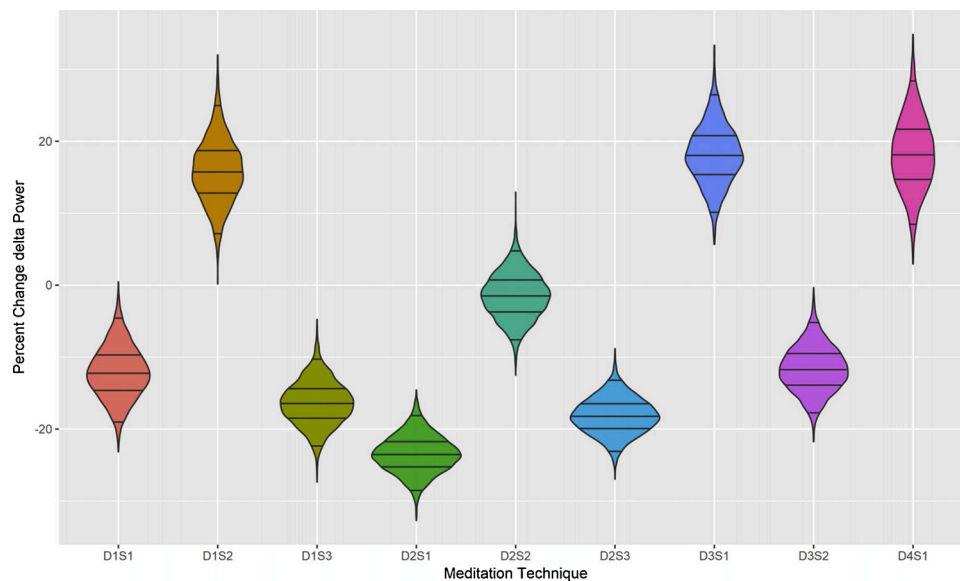


Fig. 6. Depicts violin plots of the posterior estimates for percent change in Delta power for each meditation technique, and indicates a varied effect of technique, with groups showing increases (D1S2, D3S1, D4S1), invariance (D2S2) and decreases (D1S1, D1S3, D2S1, D2S3, D3S2) in power.

% HDI = $[-0.19, -0.05]$, $[-0.23, -0.11]$, $[-0.29, -0.19]$, $[-0.23, -0.13]$, and $[-0.18, -0.05]$, respectively). Fig. 7 illustrates the main effect of electrodes with central-parietal electrodes showing more delta power than occipital electrodes and more than frontal-temporal sites. No interactions involving electrode with the other predictors were found to be credible. Fig. 7 is therefore the change in proportion due to meditation for each power band as estimated by the model's interaction between electrode and condition parameters. This effectively collapses across meditation technique including all data from all techniques as there was no credible evidence for a three-way interaction between electrode, condition, and technique.

3.12. Theta

There was a global increase in theta power of 29 % (95 % HDI = $[0.27, 0.33]$) from meditation. Results also showed a main effect of meditation technique, where D1S2 had more theta power than D2S1 and D2S3. There was also an interaction between condition and meditation technique (see Fig. 8). D1S2, D3S1, and D3S2 had the largest increases (47 %, 50 %, and 43 % with 95 % HDI = $[0.37, 0.58]$, $[0.4, 0.59]$, and $[0.34, 0.52]$, respectively) then D1S1, D2S2, and D4S1 (29 %, 33 %, and 33 % with 95 % HDI = $[0.2, 0.39]$, $[0.26, 0.41]$, and $[0.23, 0.44]$) followed by D1S3 and D2S3 (19 % and 14 %, with 95 % HDI = $[0.12, 0.27]$ and $[0.08, 0.21]$), with no credible change in theta for D2S1 (95 % HDI = $[-0.02, 0.11]$, zero included). Fig. 8 shows the effect of electrode on theta power, with midline electrodes having the most theta power followed by parietal and occipital channels, with less power at the frontal-temporal sites. There was no credible evidence for interactions involving electrode with the other predictors.

3.13. Alpha

There was a global increase of 16 % (95 % HDI = $[0.13, 0.19]$) in alpha power due to meditation. There was no credible evidence for an effect of technique with all 95 % HDI including zero. There was a credible interaction for alpha power condition between meditation technique (see Fig. 9). D1S2, D2S3, and D3S2 had the largest increases in alpha (25 %, 32 %, and 39 % with 95 % HDI = $[0.16, 0.34]$, $[0.24, 0.39]$, and $[0.29, 0.49]$) followed by D1S1, D2S1, D2S2, D3S1 (16 %, 17 %, 13 %, and 17 % with 95 % HDI = $[0.07, 0.25]$, $[0.09, 0.24]$, $[0.06, 0.2]$, and $[0.09, 0.24]$) with no credible change for D1S3 and D4S1 (95 % HDI = $[-0.09, 0.05]$, $[-0.13, 0.03]$, zero included). Fig. 9 shows the effect of electrode on alpha power, with high alpha over the occipital and parietal electrodes, no change from baseline alpha in the frontal central channels, and a decrease in the temporal sites. There were no interactions involving electrodes with the other predictors.

3.14. Beta

There was a main effect of condition, with global beta power increasing by 17 % (95 % HDI = $[0.15, 0.19]$) from pre-meditation to end-meditation. There was no main effect of meditation with all 95 % HDI including zero. However, there was an interaction between condition and meditation technique (see Fig. 10), where D1S2, D2S2, D2S3, D3S1, and D3S2 had the greatest increase in beta power (30 %, 30 %, 20 %, 32 %, and 33 % with 95 % HDI = $[0.22, 0.39]$, $[0.23, 0.38]$, $[0.14, 0.26]$, $[0.24, 0.4]$, and $[0.25, 0.41]$) followed by D4S1 (11 % with 95 % HDI = $[0.03, 0.19]$). D1S1, D1S3, and D2S1 had no credible evidence for change in beta power (95 % HDI = $[-0.06, 0.08]$, $[-0.07, 0.04]$, and $[-0.03, 0.09]$, zero included). There was also a main effect of electrodes

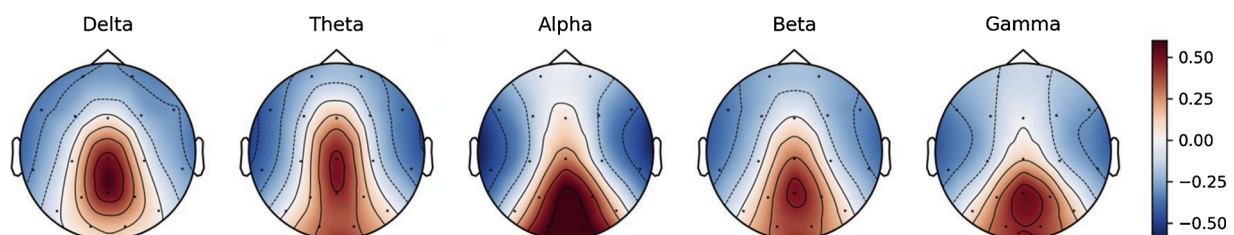


Fig. 7. Shows the overall median posterior estimate for proportion change in power band topographies.

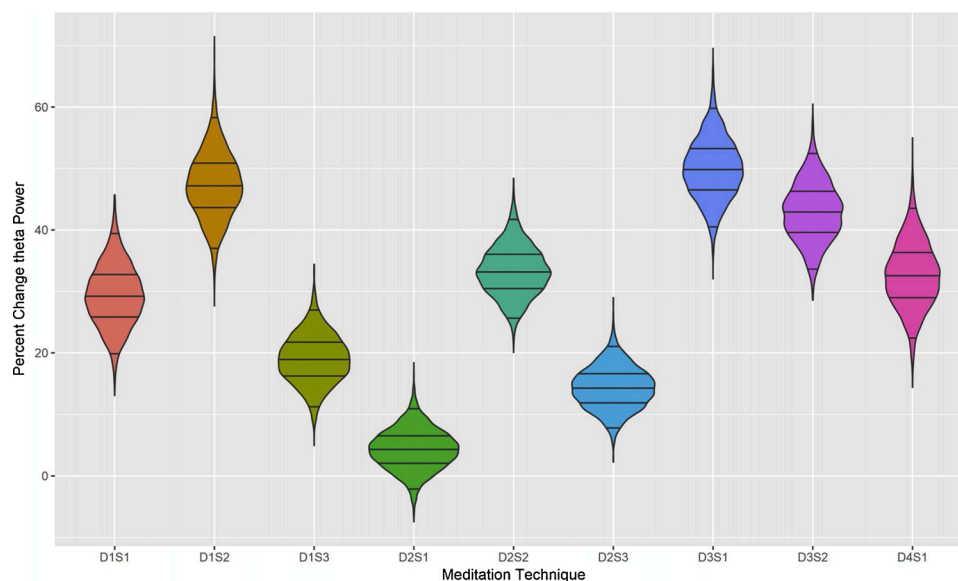


Fig. 8. Consists of violin plots of the posterior estimates for percent change in Theta power for each meditation technique. The majority of techniques increased theta power.

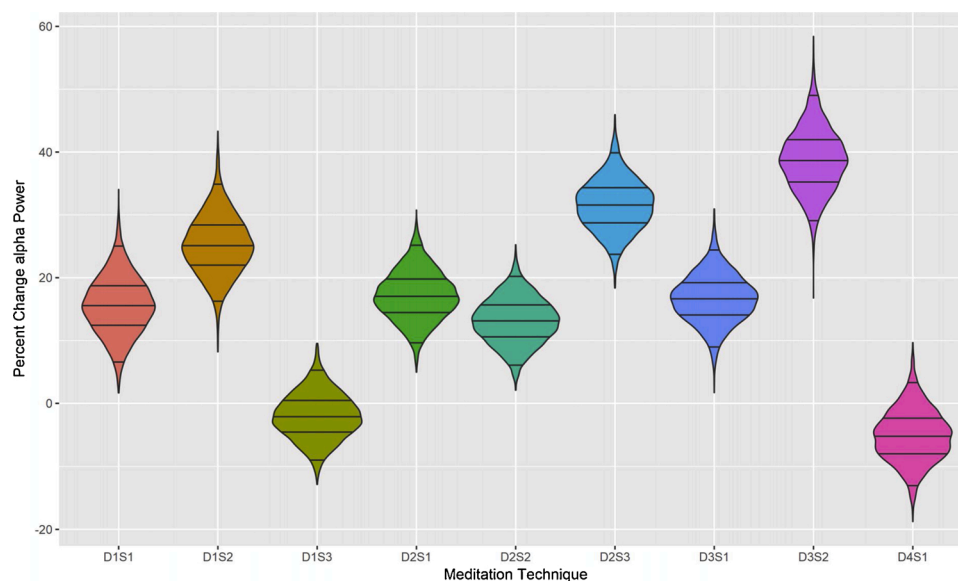


Fig. 9. Shows violin plots of the posterior estimates for percent change in alpha power for each meditation technique. The majority of techniques increased alpha power.

with more beta power over central-parietal and occipital electrodes compared to the frontal-temporal ones as shown in Fig. 10. Finally, there were no interactions involving electrodes with the other predictors.

3.15. Gamma

An 11 % increase (95 % HDI = [0.08, 0.14]) in gamma power was observed from pre-meditation to end-meditation. There was no credible evidence for a main effect of technique with all 95 % HDI including zero, indicating that the groups had similar gamma power. However, there was an interaction between technique and condition, where D1S2, D3S2, and D4S1 had the largest increase in gamma power (36 %, 31 %, and 27 % with 95 % HDI = [0.24, 0.49], [0.2, 0.42], and [0.14, 0.41]), followed by D2S2, D2S3, and D3S1 (10 %, 14 %, and 16 % with 95 % HDI = [0.02, 0.19], [0.06, 0.23], and [0.07, 0.26]), D1S3 and D2S1 did not change in gamma power (95 % HDI = [-0.07, 0.1] and [-0.14,

0.01], zero included), with D1S1 exhibiting a decrease in gamma (-17 % with 95 % HDI = [-0.25, -0.09]). There was an effect of electrode location with more gamma power over the parietal occipital electrodes compared to the frontal-central and temporal sites (see Fig. 11). Finally, there were no credible interactions involving electrodes with the other predictors.

3.16. Results summary

The machine learning model showed a high degree of accuracy for discerning pre-meditation and end-meditation EEG co-spectra for each meditation technique. The neural dynamics of each meditation technique was then assessed by applying machine learning models to the EEG co-spectra forming a classification series. This series was modelled with logistic regression, which showed the rapid transition and stabilization from pre-meditation to end-meditation EEG co-spectra. Subsequently,

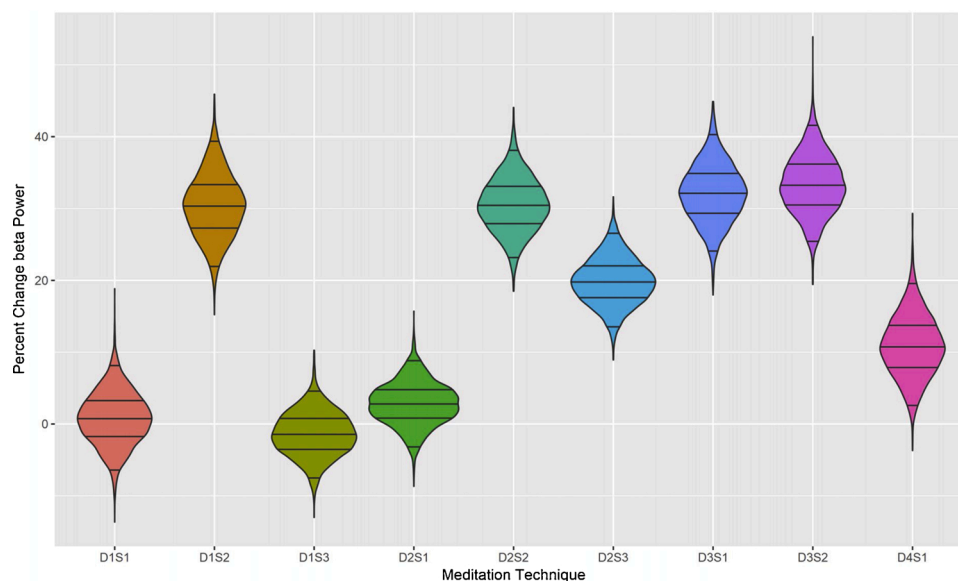


Fig. 10. Depicts violin plots of the posterior estimates for percent change in beta power for each meditation technique. The majority of techniques increased beta power, while three techniques (D1S1, D1S3, D2S1) had no change in beta power.

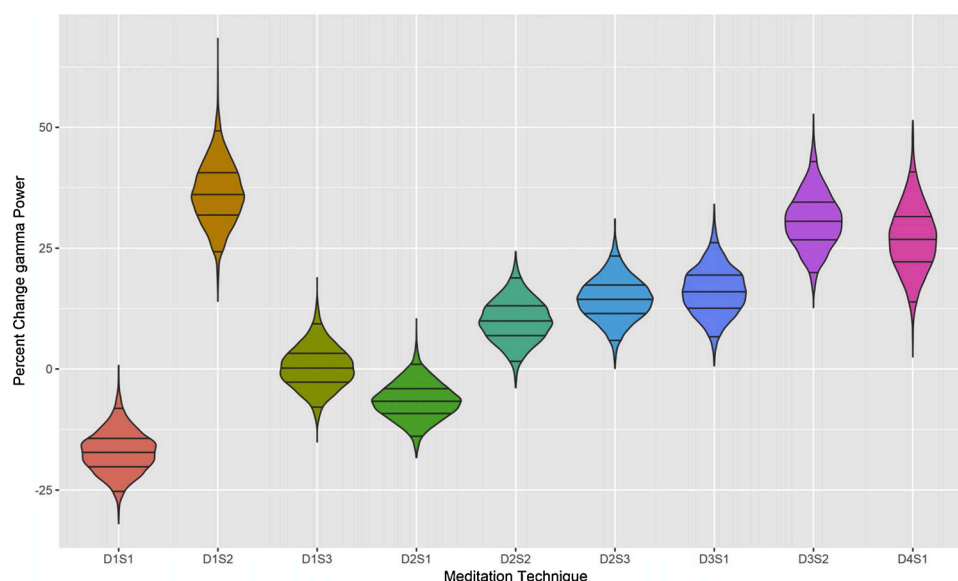


Fig. 11. Shows violin plots of the posterior estimates for percent change in gamma power for each meditation technique. The majority of techniques increased gamma power, with two techniques showing no change in gamma power and one showing a decrease.

the effect of each meditation technique was assessed for each power band by fitting a generalised linear model. This showed the heterogeneity of changes to the power bands resulting from the meditation techniques (summarised in Fig. 12).

4. Discussion

This study provided an electrophysiological examination of the impact of meditation on a sample comprising 223 novice meditators. Based on the theory of consciousness, it was hypothesized that participants would achieve altered states of consciousness observed in EEG data indicated as transformed states of brainwaves across each guided meditation. Results supported this hypothesis. Consciousness typically corresponds to the capacity to integrate information (Tononi, 2004). An integrative mode of consciousness is often typified in slow-wave theta-wave patterns that synchronize the frontal cortex with discharges

from lower brain structures, and high-frequency gamma oscillations (Winkelman, 2011). Present results indicated there was a global increase of 29 % of theta power and an 11 % increase in gamma power from pre-to end-meditation state.

Alpha activity in EEG during meditation too, has been implicated as a form of integration in the brain that leads to high-level cognitive processes (Hebert et al., 2005). This activity has been suggested to underlie the concept of the integrative mode of consciousness; that of enhanced synchronization of brain wave patterns (Winkelman, 2011). The additional aspect of meditation-induced integration in the brain is often reflected in biphasic hypersynchronous high-frequency gamma waves and the presence of gamma in meditation is a direct confirmation of the integrative model (Winkelman, 2011). This relates to the binding of diverse signals within the brain; and that gamma synchronization is modulated by the theta and alpha rhythms (Fries, 2009). Overall this study results support this model.

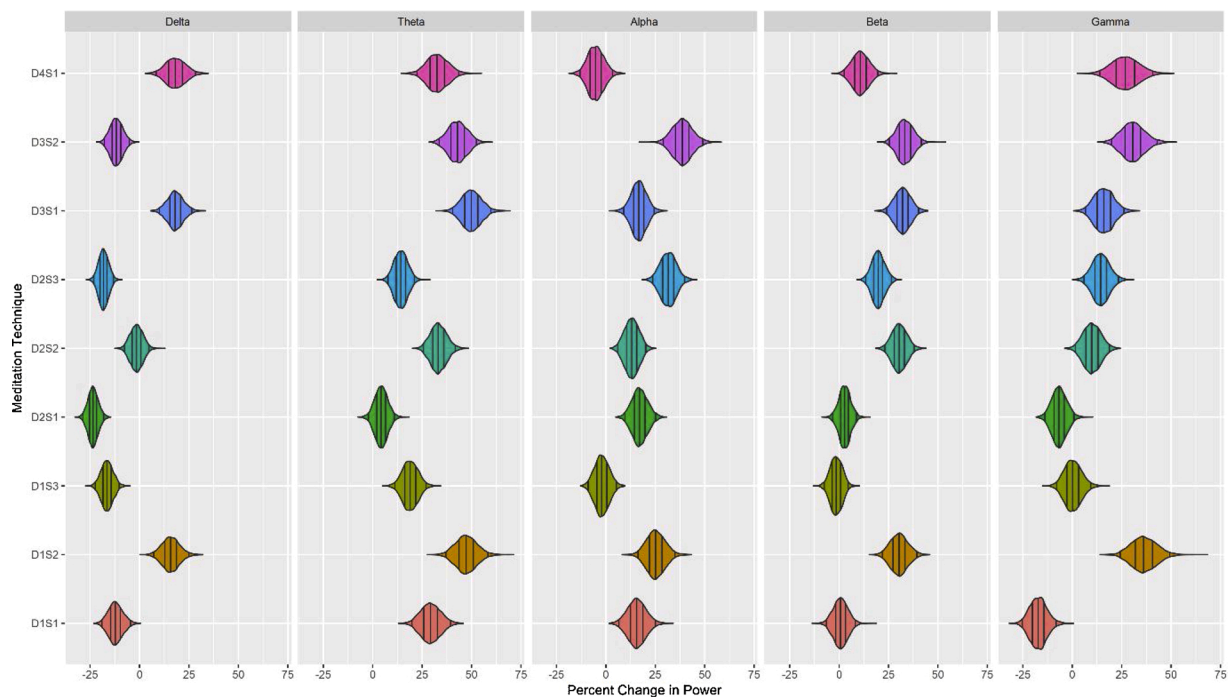


Fig. 12. Summarises the posterior estimates for percent change in power for each meditation technique and each power band. The pattern of power changes were quite varied for each technique.

Analyses suggested that EEG machine learning classifications were high, discriminating pre-meditation and post-meditation with 97 % accuracy. Differences between EEG co-spectra for pre- and post-meditation conditions were found in the sample. A relationship between time in meditation and probability of end-meditation classification was identified, with D2S2 (intending an event to materialise) faster at inducing end-meditation state than D3S2 (setting a future intention). Additionally, differences in the EEG power bands were identified, with each meditation technique inducing different patterns of changes in the power bands.

Results suggested the changing of brainwave patterns from beta brain waves (high, mid, and low range) to alpha brain waves occurred in a relatively short period. This result is consistent prior work, in which participants achieved proficiency in the attentional training aspect of meditation practice relatively quickly (Atchley et al., 2016). In the majority of participant meditation sessions, increases in beta and alpha power were observed, with alpha power more posterior over the occipital channels compared to a more parietal distribution for beta power. Further, an increase in theta power focused on the fronto-central to parietal mid-line electrodes was found.

The finding of increased gamma power at the parietal and occipital electrodes possibly originated from Brodmann's Area 30. While recent research suggests that EEG can detect subcortical sources (Seeber et al., 2019), EEG's ability to measure activity generated from such deep sources is not supported universally in the field of neuroscience (Sejnowski and Paulsen, 2006); therefore this explanation remains speculative. Regardless, this finding builds on previous studies finding increased gamma over parieto-occipital channels (Berkovich-Ohana et al., 2012; Cahn et al., 2010; Martínez Vivot et al., 2020; Schoenberg et al., 2018) by quantifying the power changes and showing rapid state change in novice meditators. While the functional role of gamma power has yet to be determined (Braboszcz et al., 2017), within the context of guided meditation, there is building evidence for a relationship to improved awareness (Cahn et al., 2010). van Lutterveld et al. (2017) used a neurofeedback paradigm to train participants to alter their gamma oscillations from the posterior cingulate cortex during meditation. It was found that gamma power was related to the subjective

experience of effortless awareness. Furthermore, a study by Voss et al. (2014) directly manipulated neural oscillations via transcranial alternating current stimulation during sleep, finding that stimulation within the gamma band increased people's awareness while dreaming. Taken together, this provides a coherent explanation of the increase in gamma over the parieto-occipital electrodes.

The demonstration of the heterogeneous effects that guided meditation techniques can have on EEG power bands underlines the relevance of using such techniques to elucidate the subjective experiences of meditators. A recent survey conducted by Vieten and colleagues (2018) showed the vast range of experiences possible during meditation. Such a range of subjective experience could be related to the differences brought about by the various meditation techniques in this study. Further research could integrate qualitative research to understand better the links among guided meditation techniques, EEG power spectra, and subjective experience.

Finally, future research providing brain imaging assessment of guided meditation training could offer critical insights. Since mindfulness has been identified as a protective factor against proactive interference and increased in hippocampal volume (Greenberg et al., 2019), future examination of guided meditation in the treatment of mental conditions characterized by impairments to working memory and hippocampal volume could have important clinical implications.

4.1. Limitations

Although this study has contributed insight into the mechanisms of change that can occur through meditation, the present findings should be interpreted in light of several limitations. Meditation session duration was varied, ranging from six to 90-min. As variability was not evenly spread across conditions (i.e., Day 2, Session 1 and Day 3 Session 1 recordings were < 10 min in duration), analysis of dynamic changes throughout meditation for these sessions was limited. Further, the current study lacked clinical measures to screen for mental health disorders among study participants. Future studies could use EEG data together with self-report measures and behavioural data to examine the relationship between the EEG patterns and positive meditation outcomes.

This study lacked a control or comparison intervention, and experimenter allegiance and bias may have been present in delivering the guided meditation. Finally, this was a convenience sample making it highly vulnerable to selection bias and the potential for sampling error.

4.2. Conclusion

The current study aimed to examine the effect of a brief guided meditation training workshop on novice meditators. Based on the theory of integrative consciousness, it was hypothesized that participants (novice meditators) would achieve altered states of consciousness detected using EEG brainwave data. Participants' pattern of brainwave power bands at each meditation end-point were compared with baseline measures (i.e., alpha, delta, and theta oscillations). Meditation competence via functional brain integration was evaluated using measures of high-frequency gamma synchronization. Overall results suggested the meditation intervention had large varying effects on EEG spectra, and the speed of change from pre-meditation to post-meditation states of the EEG co-spectra was significant therefore confirming the theory of consciousness. Findings suggest that brief guided meditation intervention may offer positive and immediate health benefits to help combat stress.

Conflicts of interest

Peta Stapleton, Stuart McGill, Debbie Sabot, Megan Peach, Danielle Raynor: No conflicts to declare.

Joe Dispenza: May be remunerated for the meditation training examined in this paper, due to expertise. Was not involved in the analysis in this paper to avoid bias.

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CRediT authorship contribution statement

P. Stapleton: Conceptualization, Methodology, Supervision, Writing - original draft. **J. Dispenza:** Conceptualization, Methodology. **S. McGill:** Formal analysis. **D. Sabot:** Writing - review & editing. **M. Peach:** Writing - review & editing. **D. Raynor:** Conceptualization.

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